Postprint of Hybrid Harmony Search and Teaching-Learning-Based Optimization Algorithm with Dynamic Selection Strategy

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Date: 2018-10-11T00:00:00+00:00

Abstract

To enhance optimization performance across diverse problem types, a hybrid optimization algorithm combining Harmony Search and Teaching-Learning-Based Optimization (HHSTL) is proposed. During different evolutionary phases, the HHSTL algorithm dynamically determines the proportion of employing either the Harmony Search algorithm or the Teaching-Learning-Based Optimization algorithm for population updating in the subsequent cycle, based on the population activity rate and the update rate of the population' s best individual. Additionally, a 'self-learning'strategy is incorporated into the standard Teaching-Learning-Based Optimization algorithm to improve its global search capability. Through simulations conducted on 16 distinct benchmark functions, comparative analysis with seven state-of-the-art algorithms, and Wilcoxon rank-sum test statistical analysis, the results indicate that the HHSTL algorithm effectively integrates the strengths of both Harmony Search and Teaching-Learning-Based Optimization, exhibiting high solution precision and robust stability, thereby enabling it to tackle a broader range of relatively complex optimization problems.

Full Text

Preamble

Title: A Hybrid Harmony Search and Teaching-Learning-Based Optimization Algorithm with Dynamic Selection Strategies

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Abstract: To improve optimization performance across various types of problems, this paper proposes a hybrid optimization algorithm based on Harmony Search and Teaching-Learning-Based Optimization (HHSTL). At different evolutionary stages, the HHSTL algorithm dynamically determines the proportion of using the Harmony Search (HS) or Teaching-Learning-Based Optimization (TLBO) algorithm as the population update method for the next cycle based on the population activity rate and the population best individual renewal rate. Additionally, a "self-study" strategy is incorporated into the standard TLBO algorithm to enhance its global optimization capability. Through simulations on 16 different types of Benchmark functions and comparative analysis with seven state-of-the-art algorithms using Wilcoxon rank sum tests, the results demonstrate that the HHSTL algorithm combines the advantages of both HS and TLBO algorithms, featuring high solution precision and excellent stability, and is capable of solving more complex optimization problems.

Keywords: Harmony Search; Teaching-Learning-Based Optimization; Dynamic Selection Strategies; "Self-Study" Strategy

Chinese Library Classification: TP301.6
DOI: 10.3969/j.issn.1001-3695.2018.06.0399

1.1 Standard Harmony Search Algorithm

The standard Harmony Search (HS) algorithm, proposed by Geem et al. in 2001, simulates the improvisation process of musicians. The algorithm proceeds as follows:

First, initialize parameters including the problem dimension D, harmony memory size HMS, maximum number of iterations $T_{\max}$, harmony memory consideration rate $HMCR$, pitch adjusting rate PAR, and pitch bandwidth Bw. Next, randomly initialize the harmony memory HM as a matrix of size $HMS \times D$ where each row represents a candidate solution. The improvisation process generates a new harmony vector X_{new} where each decision variable x^i_{new} is produced through three rules: (1) with probability $HMCR$, select from the existing values in the harmony memory; (2) with probability PAR, adjust the selected value by adding a random perturbation within the bandwidth Bw; (3) with probability $1 - HMCR$, randomly generate a value within the search space bounds. After evaluation, if the new harmony outperforms the worst harmony in the memory, it replaces that harmony. This process repeats until termination criteria are met.

To enhance HS performance, the improved HS (IHS) algorithm dynamically adjusts parameters PAR and Bw during evolution. The parameter PAR increases linearly with iterations, while Bw decreases exponentially, enabling better exploration in early stages and exploitation in later stages.

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2 Teaching-Learning-Based Optimization Algorithm

2.1 Standard TLBO Algorithm

The Teaching-Learning-Based Optimization (TLBO) algorithm, introduced by Rao et al. in 2011, mimics classroom teaching and learning behaviors. The algorithm comprises two main phases: the “Teaching” phase and the “Learning” phase.

The algorithm begins by setting parameters: NP (population size), D (problem dimension), and $T_{\max}$ (maximum iterations). The population is initialized randomly within the search space. In the Teaching phase, the best individual (teacher) shares knowledge with all students to improve the class average. Each student X_j updates according to: $X_{j,\text{new}} = X_{j,\text{old}} + \text{difference}$, where $\text{difference} = \text{rand} \times (X_{\text{teacher}} - F \times X_{\text{mean}})$. Here, X_{mean} represents the mean of all students, and the teaching factor F is randomly set to either 1 or 2. If the new solution improves fitness, it replaces the old one.

In the Learning phase, each student X_j randomly selects another student X_r for interaction. The update rule is: if $f(X_j) < f(X_r)$, then $X_{j,\text{new}} = X_{j,\text{old}} + \text{rand} \times (X_j - X_r)$; otherwise, $X_{j,\text{new}} = X_{j,\text{old}} + \text{rand} \times (X_r - X_j)$. Again, successful updates replace the original individuals.

2.2 Improvements to TLBO Algorithm

To address TLBO’ s tendency to converge prematurely and its inherent bias toward problems with optimal solutions at the coordinate origin, three enhancements are proposed:

First, the class average X_{mean} is replaced by the worst student X_{worst} in the Teaching phase. This modification, $X_{j,\text{new}} = X_{j,\text{old}} + \text{rand} \times (X_{\text{teacher}} - F \times X_{\text{worst}})$, accelerates improvement of overall class performance by targeting the weakest link.

Second, the Learning phase is modified to incorporate teacher guidance. Students now learn both from peers and from the teacher through a weighted combination: $X_{j,\text{new}} = X_{j,\text{old}} + \text{rand} \times (X_j - X_r) + \text{rand} \times (X_{\text{teacher}} - X_j)$. The weighting factor μ decreases linearly from 1 to 0 over iterations, shifting focus from peer interaction toward teacher consultation as evolution progresses.

Third, a “self-study”strategy is introduced where students independently explore subjects of interest. For each dimension i, a student performs self-adjustment with probability SCR (self-culture rate) using a step size λ, or conducts random exploration with probability SDR (self-development rate). The step size λ dynamically shrinks from $\lambda_{\max}$ to $\lambda_{\min}$ during evolution, balancing global exploration and local refinement.

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3 "Harmony-Teaching-Learning" Hybrid Optimization Algorithm

3.1 Dynamic Selection Strategy

For different optimization problems, HS and TLBO exhibit varying performance characteristics. To leverage their respective strengths effectively, a dynamic selection strategy is designed that fuses both algorithms using two mechanisms: population Activity Rate (AR) and population Best individual Renewal rate (BR). This strategy dynamically determines the proportion of HS versus TLBO for population updates in each cycle.

After every T iterations (selection period), the Dynamic Probability $DP(k)$ is recalculated for the k-th cycle. In the first cycle, both algorithms are selected with equal probability ($DP(1) = 0.5$) to ensure fair competition. In subsequent cycles, $DP(k)$ is determined by:

$$DP(k) = \frac{AR_H(k) + BR_H(k)}{AR_H(k) + AR_T(k) + BR_H(k) + BR_T(k)}$$

where $AR_H(k)$ and $AR_T(k)$ represent the activity rates of HS and TLBO respectively, calculated as the ratio of successfully updated individuals to total new individuals generated. $BR_H(k)$ and $BR_T(k)$ represent the best individual renewal rates, calculated as the ratio of times the population' s best solution is improved to the total number of populations generated.

This dynamic selection mechanism allocates higher selection probabilities to algorithms that demonstrate greater activity and contribution to optimization progress. By adapting to both the problem characteristics and algorithm performance during evolution, the hybrid approach maintains population diversity through HS while accelerating convergence through TLBO.

3.2 Algorithm Flow

The HHSTL algorithm flow is illustrated in [Figure 1: see original paper]. The procedure begins with parameter and population initialization. For each iteration, a random number is generated and compared against $DP(k)$. If the random number is less than $DP(k)$, the IHS algorithm is applied NP times to update the population and record success metrics $a_1(k)$ and $b_1(k)$. Otherwise, the improved TLBO algorithm is executed once, updating metrics $a_2(k)$ and $b_2(k)$. After T iterations, the cycle counter increments and $DP(k+1)$ is recalculated using equation (14). The process continues until the maximum fitness evaluations are reached.

4 Experimental Simulation and Testing

4.1 Experimental Environment and Parameter Settings

All experiments were conducted on a Dell PC with Intel Core i7-4790 3.6 GHz CPU and 8 GB RAM, running Windows 7 and MATLAB R2014b. To ensure fair comparison, all algorithms used the same number of fitness evaluations ($5000 \times D$). Parameter settings for the compared algorithms were taken from their original literature, as detailed in .

TABLE:1 Parameter settings for all algorithms.

4.2 Experimental Results and Analysis

The HHSTL algorithm was tested against seven competitive algorithms (DIHS, IHS, RCGHS, TLBO, ITLBO, MTLBO, TLBO-GC) on 16 diverse Benchmark functions at dimension $D = 100$. The test suite includes: F1-F3 (unimodal), F4 (hybrid), F5-F12 (complex multimodal), and F13-F16 (shifted versions of classic multimodal functions). These functions comprehensively evaluate algorithm versatility.

TABLE:2 presents the best, mean, worst, and standard deviation of results over 30 independent runs. Except for F10, all functions have theoretical optima of 0, where values closer to 0 indicate higher precision and smaller variance indicates better stability.

The results show that RCGHS, TLBO, ITLBO, and TLBO-GC achieve theoretical optima on F1, F2, F6, and F8 but perform poorly on F11-F16. DIHS reaches optima on seven functions (F4, F5, F6, F9, F11, F12, F14), while IHS does so on three functions (F10, F11, F12), but both show lower precision on F1, F2, F6, and F8. In contrast, HHSTL obtains the best mean and standard deviation across all 16 functions, demonstrating its superior ability to synthesize the strengths of HS and TLBO.

Convergence curves and box plots of optimal values over 30 runs are shown in [Figure 2: see original paper] and [Figure 3: see original paper] for $D = 100$. The convergence curves reveal that HHSTL exhibits steady downward trends on complex functions like Rastrigin Shift and Schaffer Shift, significantly outperforming competitors in global search capability and avoiding local optima. The box plots show HHSTL’ s optimal values clustering tightly, indicating excellent stability.

TABLE:3 presents Wilcoxon signed-rank test p-values comparing HHSTL against the seven algorithms, where “–” , “+” , and “ ” indicate worse, better, and equivalent performance respectively. No algorithm outperforms HHSTL on any test problem. DIHS matches HHSTL on seven problems, IHS on six, while RCGHS, TLBO, and ITLBO match on five. The majority of p-values are significantly small, confirming HHSTL’ s statistical superiority.

4.3 Analysis of Selection Period T

The selection period T controls how frequently the dynamic probability $DP(k)$ is updated. To investigate its impact, tests were conducted on six functions with varying T values at $D = 30$. **TABLE:4** summarizes mean optimal fitness values over 30 runs, and **FIGURE:4** shows distribution box plots.

The results indicate that most functions are not highly sensitive to T, with similar mean fitness across different values. The Griewank Shift Function shows slightly more variation. Based on solution precision and statistical distribution, $T = 150$ provides a balanced trade-off and is adopted as the default setting.

4.4 Analysis of Dynamic Selection Strategy

To validate the dynamic selection strategy, its behavior was examined on both unimodal and complex multimodal functions. **FIGURE:5** illustrates the evolution of $DP(k)$ during optimization.

For the unimodal Sphere Function, TLBO dominates throughout the process with a consistently higher selection probability due to its strong convergence capability. For the complex multimodal Schwefel 2.26 Function, HS receives higher selection probability in early iterations to leverage its global search ability for locating promising regions. As evolution progresses, both algorithms maintain comparable probabilities, with TLBO gaining prominence in later stages for fine-grained exploitation. This adaptive balancing maintains population diversity while accelerating convergence, demonstrating the strategy' s effectiveness.

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5 Conclusion

This paper proposes a hybrid harmony search and teaching-learning-based optimization algorithm (HHSTL) that employs a dynamic selection probability based on population activity rate and best individual renewal rate to effectively fuse the strengths of both methods. Comparative experiments on 16 diverse Benchmark functions demonstrate that HHSTL achieves high solution precision and excellent stability by capitalizing on the complementary advantages of HS' s global search capability and TLBO' s fast convergence. The algorithm shows robust performance across various problem types.

Future research will focus on developing adaptive parameter control strategies to reduce the manual tuning effort required for HHSTL' s multiple parameters. Additionally, applying the algorithm to real-world engineering optimization problems will further validate its practical utility.

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Note: Figure translations are in progress. See original paper for figures.